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***Abstract*—Magnetic induction is widely used as a non-destructive technique to detect and classify metal objects over a range of applications. This paper applies magnetic induction spectroscopy (MIS) as a technique to classify non-ferrous metals within shredded metal waste streams on a moving conveyor. The magnetic response of the metal piece as it passes over the sensor is used to predict the metal, where the measured complex impedance components are used as features for the machine learning models. MIS performs well even when surface contaminants are present, compared to other techniques that require the metal pieces to be cleaned; this saves time and cost when large amounts of surface contamination are present in a waste stream, such as biomass incinerator metals. MIS allows for a lower cost system when compared to X-ray and float-sink methods, with a high throughput which makes it an economical approach.**

***Index Terms*—Magnetic induction spectroscopy, non-destructive evaluation, recycling, non-ferrous, batteries.**

I. Introduction

NON-FERROUS metals need to be recovered from waste streams to be recycled and reused. An ideal system that recovers non-ferrous metals must be accurate and process a large throughput, which will help to make it economical. A system that can recover non-ferrous metals efficiently will assist in moving the world to a more sustainable 'circular economy' [1]. In addition to the economic benefits, there is an environmental benefit too. For example, it can take 17 times more energy to produce 1000 Kg of aluminium from virgin ore compared to recycled aluminium [2].

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Non-ferrous metals must be removed from a waste stream and sorted into elements, such as copper, brass and aluminium. Some metals, such as aluminium, will also need to be further sorted into their alloy families. Sorting aluminium into alloys is a complex process as tramp elements (contaminants) make it difficult to recycle the metal if there is cross-contamination [3]. Cross-contamination of alloy families can affect the metal properties, such as making the metal brittle [3].

Manual sorting is a common approach that has been used, especially in developing countries, where workers use the colour and physical characteristics to determine the metal [4]. Manual sorting is only economical when labour costs are low; this has led Europe and the United States to export their waste to developing countries, which has grown substantially over the last 20 years [4]. The accuracy of manual sorting depends on the worker and their experience, but it is claimed that it can achieve accuracies up to 99% [5].

There are other methods available to separate non-ferrous metals. In industry, a combination of these depends on the scrap metal mix and the desired metals. Before the sorting techniques, large sieves are used to separate the metal into sizes; these tend to be 3-8 mm, 8-25 mm and 25 mm+. The sieves provide a very coarse separation as long thin items can still pass through along with other shapes, however this still allows the metal sizes to be crudely controlled. The metals in the waste streams can also be controlled and are assigned names related to their sources, such as fridge metals, window frames and biomass incinerator metals (BIM). Other waste stream names such as Zorba and Zurik are less clear [6]. Zorba consists of shredded non-ferrous metals and is predominantly aluminium, and Zurik is predominantly stainless steel [6].

Sink float systems use the different densities of metals for separation. Separation is achieved by slurries of water, sand and air used to create different gravitational drums that separate the metal [4]. Sink float is commonly used to separate heavy metals (copper and brass) from the lighter metal (aluminium). Sink float has additional costs such as the maintenance of the gravitational density and the associated environmental waste [4]. X-ray transmission (XRT) can distinguish the metals based on density; this is achieved by an x-ray image of the metal [7]. Both XRT and sink-float techniques suffer from poor separability of metals with similar densities; however, they benefit from minimal/no performance degradation when metals have surface contaminants [8], [9].

A benefit of sink float systems is that it can reduce the quantity of scrap metal processed by a gold-standard method. The gold-standard methods, which work by scanning metal pieces as they pass by on a conveyor belt, will increase in price as the width of the conveyor increases. The gold-standard approach to classify non-ferrous scrap metal is Laser-Induced Breakdown Spectroscopy (LIBS) and X-ray fluorescence (XRF). LIBS and XRF can classify the metal's compositions, making them commonly used for handheld analysers [10] . A limitation of these methods is the high throughput required for the industrial application, where a typical conveyor operates at speeds between 2 to 3 m/s.

When using LIBS the speed of the conveyor makes it difficult to target the laser, which also requires multiple shots to remove surface contaminants such as paint and dirt [7], [11]. The surface contamination must be removed when using LIBS, otherwise the composition of the contamination will be detected. The surface contamination can be removed prior to LIBS, but this increases time and cost.

Where LIBS uses a laser as a firing source, XRF emits X-rays [12]. Like LIBS, XRF is susceptible to surface contamination as the x-ray radiation hits the contamination first. The metal pieces can be cleaned prior, but this can take time and have a high cost, especially when the quantity of metal needed to be processed is considered. Metals with low-energy characteristic, such as aluminium, silicon and magnesium, can be difficult for the XRF to classify [4]. The main alloy elements are used to determine the spectral ratio of aluminium alloys due to the low radiation characteristic [4].

Manual sorting can be automated with a camera. A hyperspectral imaging (HSI) camera will provide wavelengths beyond the RGB spectrum that a standard camera provides. HSI methods have achieved classification accuracies of 96.87% [13] and 98.36% [14] with WEEE scrap metal and 80 to 97% for brass, iron, copper, aluminium, and nickel classification [15]. HSI has high dimensional vectors for each pixel, which increases the computation required [13]. Slower computation will require a slow conveyor, but speeds of 2.28 m/s have been reported quicker than previous <1 m/s [13]. A limitation of optical systems is industrial conditions, which is difficult to control, such as ambient light, reflections and dust.

Another approach to sorting non-ferrous metals is magnetic induction-based sensors, which are suitable for conveyors that process a large throughput. Unlike XRF, LIBS and vision methods, magnetic induction is largely unaffected by surface contaminants. As well, induction sensors not require a line of sight to the sample; this means the sensors can be placed under the conveyor. The conveyor speed poses a challenge, as the faster the belt speed, the fewer measurements an induction coil can take. As well, the faster conveyor requires the processing and classification of the measurements to be quicker. A fast conveyor makes the induction system more economical as it can process more waste. A slower conveyor belt can be used but would require a wider conveyor to ensure the same throughput, but it will increase the system's price.

Ideally the sensor must be close the metal sample as it is affected by the lift-off of the metal sample [16], which can be difficult as the conveyor belt bounces and the pieces may roll. The difficulties of lift-off is further exacerbated by the irregularity in the metal geometry. Scrap waste streams tend to be grouped into size, such as 3-8 mm and 8-25 mm, which allows consistency of size. However, as the metal scrap is shredded the geometry of the pieces vary, which can lead to different lift-offs between samples and across the sample.

Low-frequency (700 Hz and 5 Khz) and pulsed magnetic fields have been researched for sorting non-ferrous metals by Messina et al. [9], [17]. The system had good results when there was a large difference in the conductivity of the metals. Recovery and purity rates between 90 and 100% were reported for stainless steel. However, recovery and purity were below 80% for the other metals.

The induction can be combined with other sensors to improve results. Kutila et al. [18] combined induction sensors with optical sensors. The addition of a camera gave a range of 80% to 95% purity and recovery rates for stainless steel, copper, and brass. Another approach was to use a dual-frequency system, where O'Toole et al. used excitation frequencies between 3 kHz and 64 kHz [19]. The dual-frequency system produced 92% on average for purity and recovery when the system used pre-cut pieces. When the system used commercial waste, the accuracy fell to 80 to 90% recovery and 55% to 92% purity [11].

This paper explores the research process of the use of magnetic inductions sensors to classify non-ferrous metals. Early results will be discussed and compared to new developments that use multi-frequency MIS combined with colour, which is classified by different machine learning techniques. This paper will review the challenges faced by magnetic induction and the limitations of an induction system. Finally, the paper will discuss future work and research, which include combining the induction sensors with other sensors for the non-destructive evaluation of scrap non-ferrous metals.

II. Theory

A. *Magnetic induction spectroscopy*

This section presents how magnetic induction is used for classification and show an analytic formula that visualises the expected results. An induction sensor is used for classification, which consists of a transmit and receive coil. The transmit coil will excite a describes magnetic field at a given frequency. When the metal is inside the magnetic field, eddy currents

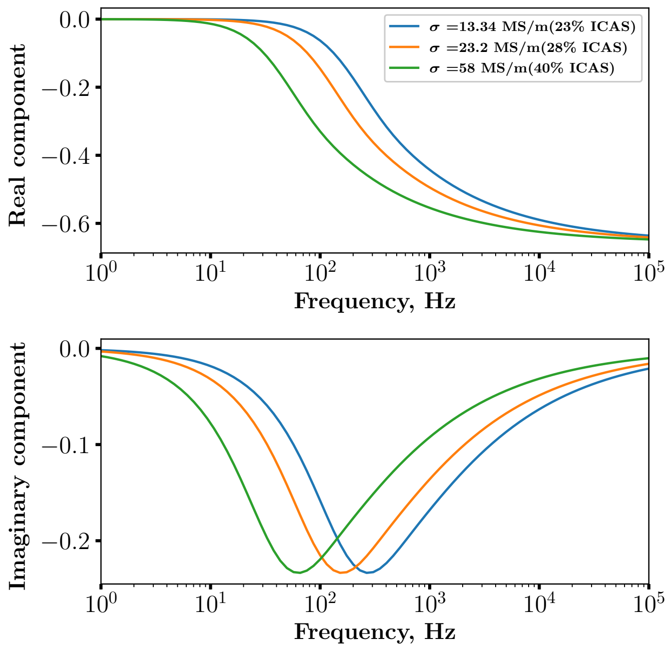

Fig. 1. The real and imaginary components of three conductive spheres, with a radius of 20 mm, where the conductivity changes.

are induced, which flow in the azimuthal direction [20]. The resultant eddy currents induce a secondary magnetic field measured by the receive coil. The shape and conductivity of the metal piece affect the secondary magnetic field.

To further understand how magnetic induction spectroscopy can be used to determine the conductivity of different metals the analytical formulation of a conductive sphere in free space can be used [21]. The equation has been used in previous work to explain the effect that conductivity σ, frequency f, and radius a have on the spectral response [19]. The equation calculates the complex components of the secondary H_{rx} and excitation H_{ex} magnetic field at point z along the Z-axis, which is outside the sphere ($z > a$). An example of the effect conductivity has on the spectra of a curve can be seen in Fig. 1, which was calculated with (1).

$$\frac{H_{rx}}{H_{ex}} = -\frac{3a^3}{z^3}\left(\frac{1}{\alpha^2} + \frac{1}{3} - \frac{\cosh\alpha}{\alpha\sinh\alpha}\right) \tag{1}$$

$$\alpha = (i2\pi f\sigma\mu)^{\frac{1}{2}}a$$

Fig. 1 shows that all curves will start with a low-frequency inductive component at 0, then fall to the same real asymptote, where the eddy current flow closest to the surface [22]. The only notable difference with the real component observed in Fig. 1 is when the curves are falling. Fig.1 shows that the peak of the imaginary component will occur lower in frequency as the conductivity increases.

III. Results and Discussions

This section discusses the results and findings of initial research on using magnetic induction to classify non-ferrous metals. Then newer results that use the MetalID coil [11] and machine vision are reviewed for the efficacy of colour for classification. Finally, potential future research are explored and the challenges evaluated.

The magnetic induction coils were used [19] as part of an EU project Shreddersort (No. 603676). The industrial system developed used a combination of sensors, which combined an array of induction sensors and a vision image analysis system. The induction coil used a two-frequency approach that provided good results with 92% on average for purity and recovery when the system used pre-cut pieces. These results showed the potential of magnetic induction to sort scrap metal. O'Toole et al. [19] also showed a low performance of a combined vision and induction system, which used only simple geometric features such as area and height. It was clear that using sample geometry was more complicated than the scope of that work. The cheapness of induction sensors is also highlighted compared to other sensing methods, which is an economic incentive.

The dual-frequency approach was further explored in O'Toole et al. [11] using the new MetalID coil design. The dual frequency approach was based on observation that lower frequency measurements are sensitive to shape and conductivity of a sample, whereas higher frequency is only dependent on shape due to negligible skin-depth. The work used scrap metal which allowed for more representative pieces but resulted in an unknown liftoff due the more variable shape [11].

O'Toole et al. [11] found that the scrap metal samples' responses overlapped more than in previous work. The new pieces led to a reduced recovery and purity rate of 80% and 80% for copper and 80% and /75% for brass. The aluminium classification had the lowest result with 80% and 55% recovery and purity. The low accuracy shows the importance of using shredded scrap metal sourced from waste streams, as pre-cut metals can give artificially better results.

A conclusion of [11] was to use multiple frequency components to provide more features for classification algorithms. Initially, the results used a linear regression model, but it was noted that the use of more complex algorithms might improve the accuracy. O'Toole et al. [11] used a binary classification process; this is important as on an industrial conveyor, air jets are used to shoot the metal pieces into a bin or allow them to drop.

Williams et al. [23] extended the work of O'Toole et al. [11] by using a broader frequency spectrum and comparing multiple machine learning techniques. In addition, the efficacy of colour as a feature was assessed to see if it could improve the classification accuracy. The measurements were taken on a static rig which allowed the camera to be positioned above the induction sensor. The static rig separated the top of the coil from the metal samples with 3 mm of acrylic. The scrap metal pieces were sourced from industrial waste streams to ensure the results were representative. The paper classified stainless steel, brass, zinc and aluminium, whereas previous work focused on copper, brass and aluminium.

Stainless steel results showed >99% recovery and >93%

purity, which was the highest of all the metals. When brass was classified within biomass incinerator metals (BIM), a recovery of 97% and purity of 83% was obtained. The samples within BIM all had surface contamination and the results showed that surface contamination did not affect the induction coil, which typically affects systems such as LIBS and XRF. Zinc obtained 81% recovery and 77% purity when classified within the window frame waste stream. The aluminium results looked promising with recovery rate >89% and purity rates of >81%, which is an improvement on the previous aluminium results [11]. The worst results came from brass and aluminium classified within 8-25 mm Zorba. Poor results of 54% recovery and 53% purity for brass and 70% and 52% for aluminium were obtained. The poor result were due to the aluminium pieces consisting of cast aluminium which has a conductivity of 23% ICAS [24], similar to brass which has a conductivity of 26% [25]. These results shows a limitation of induction sensors, which is that they will struggle to distinguish between metals with a similar conductivity.

When the induction spectra was measured, an image of the sample was taken to extract its colour in the RGB and HSV colour space. The colour would be used as a feature for machine learning algorithms. The addition of colour improved most waste streams apart from three. A waste stream that did not improve was those that contained stainless steel, as the induction results had already classified the metal with high accuracy. The other waste stream that did not improve was the BIM waste stream, where all the pieces had surface contamination which gives all the piece a similar colour, making colour redundant. The addition of colour improved the accuracy significantly with the 3 to 8 mm Zorba pieces, which previously had the lowest accuracy. The result showed that additional sensors like a camera should be used when the conductivity is similar. The recovery and purity rate obtained through the different methods for sorting non-ferrous metals are shown in Fig. 2. The number of target metal and non-target metals for the different methods are listed in Table I.

Another application of the induction sensors for resource recovery was research by Williams et al. [26] which looked into using the inductive response of batteries for sorting into the size and internal contents. The results showed different induction spectra for each battery depending on its size, allowing D and E-sized batteries to be sorted from AA and AAA. Though a camera could easily sort by size, induction could be used if there is no line of sight or the battery is placed inside a non-metallic enclosure.

The induction spectra of AA were reviewed to determine the internal contents of a AA battery for safety or sorting. Some batteries contain lithium which can combust when exposed to moisture when incorrectly discharged. Therefore, induction sensors could be used to detect and remove lithium batteries before they are shredded. Fig. 3 shows the real component of different AA batteries when placed vertically. Fig. 3 shows that the real response of the battery allowed for the clear identification of zinc and zinc chloride batteries. It can also be observed that when the battery was placed vertically, the real

TABLE I
TOTAL NUMBER OF TARGET AND NON-TARGET METAL SAMPLES USED IN REPORTED RESULTS

Reference	Metal	Target/Non-Target metal samples	Fig. 2 label
Classification of nonferrous metals using magnetic induction spectroscopy [19]	Copper	36/81	Cu1
	Brass	37/80	Br1
	Aluminium	44/73	Alu1
Classification of Non-ferrous Magnetic Scrap Metal using Two Component Induction Spectroscopy [11]	Copper	98/149	Cu2
	Brass	100/147	Br2
	Aluminium	49/198	Alu2
Scrap metal classification using magnetic induction spectroscopy and machine vision [23]	Stainless steel (8-25 mm Zurik)	33/13	Ssteel1
	Stainless steel (25-75 mm Window frame)	14/22	Ssteel2
	Brass (Biomass incinerator metals)	73/19	Br3
	Brass (3-8 mm Zorba)	30/58	Br4
	Zinc (window Frame)	33/60	Zn
	Aluminium (8-25 mm Window Frame)	55/37	Alu3
	Aluminium (3-8 mm Zorba)	30/58	Alu4
	Aluminium (25-75 mm Fridge metals)	60/31	Alu5
	Aluminium (25-75 mm Window Frame)	14/22	Alu6

component had two distinct groups between the other batteries. The nickel-metal hydride (NiMH) and lithium batteries has a similar response compared to alkaline; this would allow them to be separated and possibly extracted.

Williams et al. [26] showed that all batteries, apart from AA Zinc, could be differentiated from scrap non-ferrous and stainless steel. The difference would allow batteries to be extracted from mixed metal waste streams where they would contaminate the metal. The induction has the potential to work well if the batteries are present inside non-metallic objects, like toys, where an optical system requires a line of sight.

The results presented in this paper show the potential of magnetic induction to sort different waste streams. The recent results shown have used a broad frequency spectrum; however, in an industrial system, only a limited number of frequencies can be used as the energy per frequency decreases when more frequencies are excited. As well, it can become challenging to measure low frequencies as the fast moving pieces will pass over the sensor before enough time has passed to measure and process the signals. Therefore it is essential to reduce the number of frequencies used, which may depend on the metal and waste stream. The results have shown the importance of colour in improving the classification accuracy, but the importance of other geometrical features such as shape may be helpful for the algorithms. The new shape features would have to be more developed than those recorded in [19] as these did not improve the accuracy.

Finally, [23] explored machine learning algorithms for classification. Caution must be taken as the best algorithm may be complex and take a long time to compute; this is further limited as the algorithm would be operating on a small microcontroller or DSP device. The long computation time will become a challenge as only a few milliseconds are allowed before a prediction is needed. A longer prediction

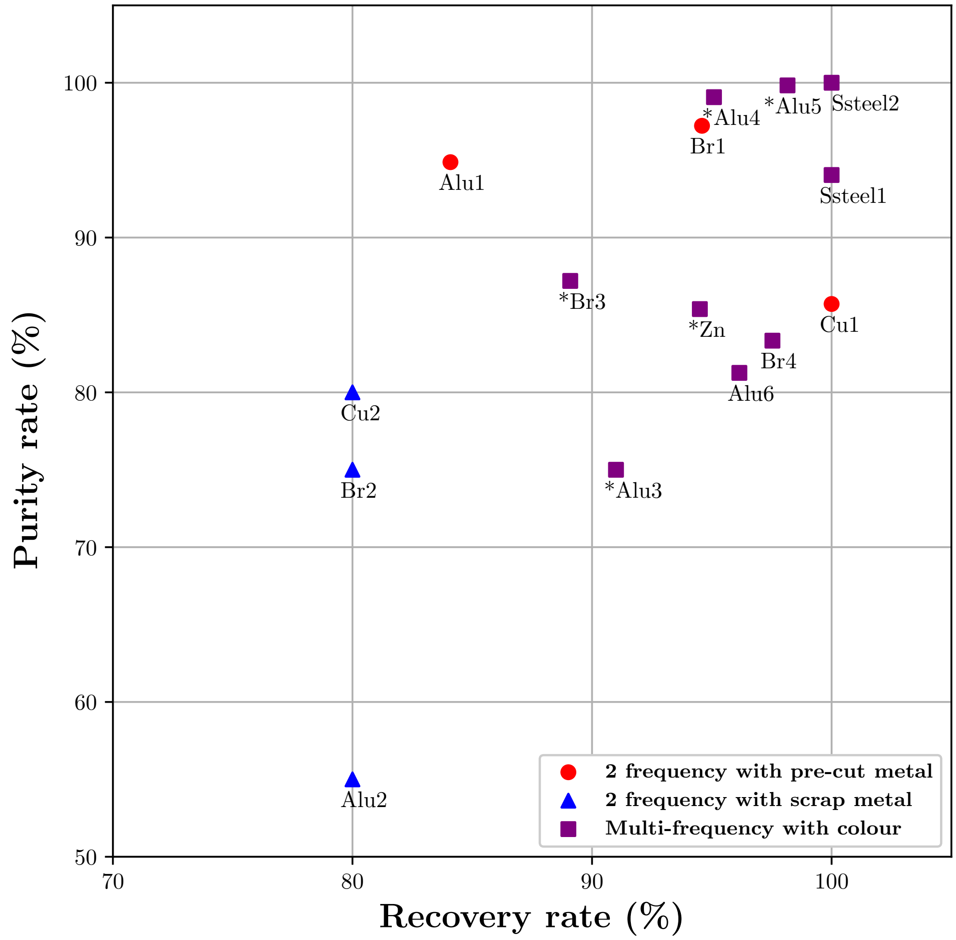

Fig. 2. Recovery and purity rate results across all 3 papers of different metals [11], [19], [23]. The waste steams used and corresponding label is given in Table I. *Indicates that the result used colour as an additional feature to improve the result.

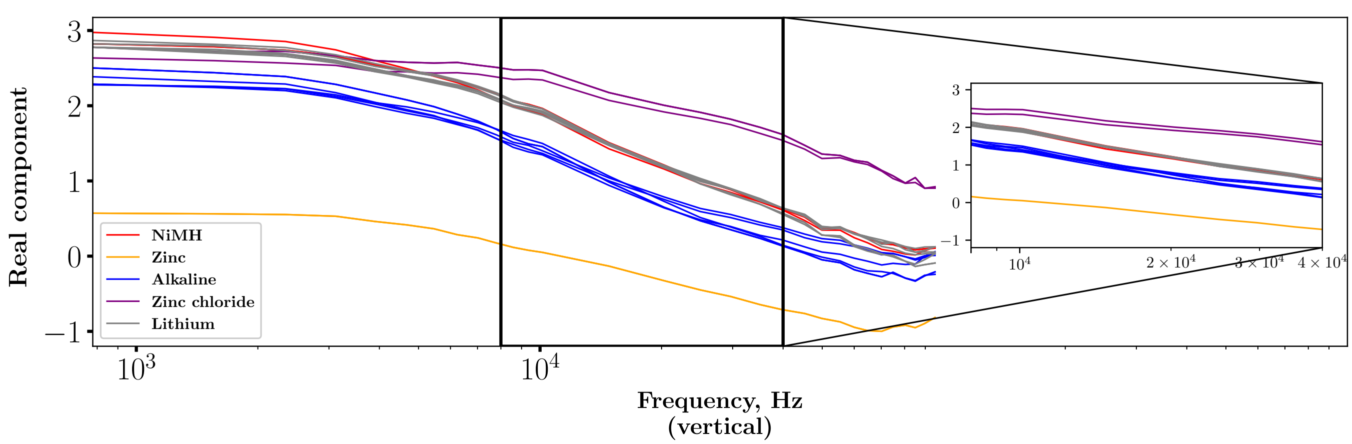

Fig. 3. The real response of different AA batteries between 780Hz and 95282 Hz when the battery is placed vertically. The figure was first reported in [26] and has been edited to highlight the region with the largest difference.

time would require the conveyor to move slower and reduce the throughput, potentially making the system uneconomical.

IV. Conclusion

Magnetic induction offers an approach to sort non-ferrous metals and other metallic waste, such as batteries. Induction has the benefit of penetrating the surface of the metal, reducing the effect of surface contamination and not requiring metal pieces to be cleaned, which decreases the cost and time to process the scrap metal. However, if the surface contamination thickness was large this can increase the lift-off between the metal and coil reducing the measurements.

Initial results obtained achieved promising results. However, this was with pre-cut pieces that can give artificially better results; this was seen when shredded scrap metal was used, and there was a decrease in accuracy. Further research was carried out to see if a broader frequency spectrum would improve the results compared to the previous dual-frequency approach. Additionally, the study looked into the efficacy of colour as a feature to improve results. Induction alone was able to classify metals with large conductivity and permeability differences, like stainless steel, and metals with surface contamination such as those produced from a biomass incinerator. However, induction alone did not achieve accurate results for metals with similar conductivities. When colour was added as a feature, the accuracy improved for all metals, apart from those with stainless steel present or surface contaminants. The most significant improvement due to the addition of colour was the 3 to 8 mm Zorba pieces, where the conductivity of the metals was similar. The 3 to 8 mm Zorba showed that induction makes it difficult to separate metals of similar conductivities difficult.

Research has also shown that magnetic induction could separate batteries based on size or internal contents. Differentiating between batteries would allow for efficient recycling or a safety feature to stop lithium batteries from being shredded and potentially causing fires.

The efficacy of induction will be continued to be investigated and scrutinised, as well as different sensors to provide more features to improve the accuracy. Future results will need to be obtained with industrial scrap and on a conveyor system to give a more representative result of industry conditions. For induction to work on an industrial system, an array of coils must be used to ensure that the whole width of the conveyor is covered by at least one sensor, similar to previous work [19]. In addition, an ejection method must cover the width of the conveyor, such as air ejectors, to ensure any metal sample can be removed from the waste stream regardless of position.

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